High-Resolution Spectrum-Estimation Methods for Signal Analysis in Power Systems

Tadeusz Lobos, Zbigniew Leonowicz, *Member, IEEE*, Jacek Rezmer, and Peter Schegner, *Member, IEEE*

***Abstract*—The spectrum-estimation methods based on the Fourier transform suffer from the major problem of resolution. The methods were developed and are mostly applied for periodic signals under the assumption that only harmonics are present and the periodicity intervals are fixed, while periodicity intervals in the presence of interharmonics are variable and very long. A novel approach to harmonic and interharmonic analysis based on the "subspace" methods is proposed. Min-norm and music harmonic retrieval methods are examples of high-resolution eigenstructure-based methods. Their resolution is theoretically independent of the signal-to-noise ratio (SNR). The Prony method as applied for parameter estimation of signal components was also tested in the paper. Both the high-resolution methods do not show the disadvantages of the traditional tools and allow exact estimation of the interharmonic frequencies. To investigate the methods, several experiments were carried out using simulated signals, current waveforms at the output of an industrial frequency converter, and current waveforms during out-of-step operation of a synchronous generator. For comparison, similar experiments were repeated using the fast Fourier transform (FFT). The comparison proved the superiority of the new methods.**

***Index Terms*—Eigenvalues and eigenfunctions, harmonic analysis, industrial power-system harmonics, inverters, signal resolution, synchronous-generator transient analysis, time-frequency analysis.**

I. Introduction

TODAY, the quality of voltage waveforms is an issue of utmost importance for power utilities, electric energy consumers, and also for manufacturers of electric and electronic equipment. The liberalization of energy markets will strengthen the competition and is expected to drive down the energy prices. This is the reason for the requirements concerning the power quality. The voltage waveform is expected to be a pure sinusoidal with a given frequency and amplitude. Modern frequency power converters generate a wide spectrum of harmonic components that determine the quality of the delivered energy and increase the energy losses as well as decrease the reliability of a power system. In some cases, large converter systems generate not only characteristic harmonics typical for the ideal converter operation but also a considerable amount of noncharacteristic harmonics and interharmonics, which may strongly determine the quality of the power-supply voltage [1], [2]. The estimation of the components is very important for control and protection tasks.

There are many different approaches for measuring harmonics like fast Fourier transform (FFT), application of adaptive filters, artificial neural networks, singular value decomposition (SVD), higher order spectra, etc. [3]–[7]. Most of these approaches operate adequately only in the narrow range of frequencies and at moderate noise levels. Estimation of the power spectral density (PSD) or simply the spectrum of discretely sampled deterministic and stochastic processes is usually based on procedures employing the FFT. The most often-used spectral-estimation techniques are the following:

1) indirect approach via an autocorrelation estimate (Blackman–Tukey);
2) direct approach via FFT operation (periodogram);
3) modified averaged periodogram (Welch).

The conventional FFT spectral estimation is based on a Fourier-series model of the data, that is, the process is assumed to be composed of a set of harmonically related sinusoids. This approach to spectrum analysis is computationally efficient and produces reasonable results for a large class of signal processes. In spite of these advantages, there are several inherent performance limitations of the FFT approach. The most prominent limitation is that of frequency resolution, i.e., the ability to distinguish the spectral responses of two or more signals. Because of some invalid assumptions (zero data or repetitive data outside the duration of observation) made in this method, the estimated spectrum can be a smeared version of the true spectrum [8].

A second limitation is due to noncoherent signal sampling of the data, which manifests itself as a leakage in the spectral domain—energy in the main lobe of a spectral response leaks into the side lobes, obscuring and distorting other spectral responses that are present. Windowing is used to reduce the leakage, but it introduces additional distortions.

These two performance limitations of the FFT approach are particularly troublesome when analyzing short data records. Short data records occur frequently in practice because many measured processes are brief in duration or have slowly time-varying spectra, which can be considered constant only for short record lengths. These methods usually assume that only harmonics are present and the periodicity intervals are fixed, while periodicity intervals in the presence of interharmonics are variable and very long [1].

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The Prony method is a technique for modeling sampled data as a linear combination of exponentials. Although it is not a spectral-estimation technique, the Prony method has a close relationship to the least squares linear prediction algorithms used for autoregressive (AR) and autoregressive-moving-average (ARMA) parameter estimation. The Prony method seeks to fit a deterministic exponential model to the data in contrast to AR and ARMA methods that seek to fit a random model to the second-order data statistics. In [9], a new method of real-time measurement of power-system frequency based on the Prony model is presented.

The most recent methods of spectrum estimation are based on the linear algebraic concepts of subspaces and have been called "subspace methods" [10]. Its resolution is theoretically independent of the signal-to-noise ratio (SNR). The model of the signal in this case is a sum of random sinusoids in the background of a noise of a known covariance function. Pisarenko first observed that the zeros of the z transform of the eigenvector, corresponding to the minimum eigenvalue of the covariance matrix, lie on the unit circle and their angular positions correspond to the frequencies of the sinusoids. In a later development, it was shown that the eigenvectors might be divided into two groups, namely, the eigenvectors spanning the signal space and the eigenvectors spanning the orthogonal noise space. The eigenvectors spanning the noise space have eigenvalues that are the smallest and that equal to the noise power. One of the most important techniques, based on the Pisarenko approach of separating the data into signal and noise subspaces, is the min-norm method.

To investigate the ability of the methods, several experiments were performed. Simulated signals and current waveforms at the output of an industrial frequency converter as well as current waveforms during out-of-step operation of a synchronous generator were investigated. For comparison, similar experiments were repeated using the FFT.

In this paper, the frequencies of signal components are estimated using the Prony model and the min-norm subspace method.

In other publications, the authors investigated different aspects of signal analysis in power systems. In [11], the main part was devoted to the investigation of the frequency converter with emphasis to real signals, whereas in [12], only some cases of simulated industrial frequency converters were reported. This paper presents the case of out-of-step operation of synchronous generators, the analysis of waveforms from the power supply of dc arc furnaces, and the detailed analysis of frequency converters as examples of analysis using the Prony and min-norm methods in power systems.

II. Prony Method

Assuming the N complex data samples $x[1], \ldots, x[N]$; the investigated function can be approximated by M exponential functions

$$y[n] = \sum_{k=1}^{M} A_k e^{(\alpha_k + j\omega_k)(n-1)T_p + j\psi_k} \tag{1}$$

where $n = 1, 2, \ldots, N$; T_p is the sampling period; A_k is the amplitude; α_k is the damping factor; ω_k is the angular velocity; and ψ_k is the initial phase.

The discrete-time function may be concisely expressed in the form

$$y[n] = \sum_{k=1}^{M} \mathbf{h}_k \mathbf{z}_k^{n-1} \tag{2}$$

where

$$\mathbf{h}_k = A_k e^{j\psi_k}, \quad \mathbf{z}_k = e^{(\alpha_k + j\omega_k)T_p}.$$

The estimation problem is based on the minimization of the squared error over the N data values

$$\delta = \sum_{n=1}^{N} |\, \varepsilon[n]|^2 \tag{3}$$

where

$$\varepsilon[n] = x[n] - y[n] = x[n] - \sum_{k=1}^{M} \mathbf{h}_k \mathbf{z}_k^{n-1}. \tag{4}$$

This turns out to be a difficult nonlinear problem. It can be solved using the Prony method that utilizes linear-equation solutions. If as many data samples are used as there are exponential parameters, then an exact exponential fit to the data may be made.

Consider the M-exponent discrete-time function

$$x[n] = \sum_{k=1}^{M} \mathbf{h}_k \mathbf{z}_k^{n-1}. \tag{5}$$

The M equations of (5) may be expressed in matrix from as

$$\begin{bmatrix} \mathbf{z}_1^0 & \mathbf{z}_2^0 & \cdots & \mathbf{z}_M^0 \\ \mathbf{z}_1^1 & \mathbf{z}_2^1 & \cdots & \mathbf{z}_M^1 \\ \vdots & \vdots & & \vdots \\ \mathbf{z}_1^{M-1} & \mathbf{z}_2^{M-1} & \cdots & \mathbf{z}_M^{M-1} \end{bmatrix} \cdot \begin{bmatrix} \mathbf{h}_1 \\ \mathbf{h}_2 \\ \vdots \\ \mathbf{h}_M \end{bmatrix} = \begin{bmatrix} x[1] \\ x[2] \\ \vdots \\ x[M] \end{bmatrix}. \tag{6}$$

The matrix equation represents a set of linear equations that can be solved for the unknown vector of amplitudes. Prony proposed to define the polynomial that has the $\mathbf{z}_k$ exponents as its roots

$$F(\mathbf{z}) = \prod_{k=1}^{M} (\mathbf{z} - \mathbf{z}_k) = (\mathbf{z} - \mathbf{z}_1) \cdot (\mathbf{z} - \mathbf{z}_2) \cdot (\cdots) \cdot (\mathbf{z} - \mathbf{z}_M). \tag{7}$$

The polynomial may be represented as the sum

$$F(\mathbf{z}) = \sum_{m=0}^{M} a[m]\mathbf{z}^{M-m} = a[0]\mathbf{z}^M + a[1]\mathbf{z}^{M-1} + \ldots + a[M-1]\mathbf{z} + a[M]. \tag{8}$$

Shifting the index on (5) from n to $n-m$ and multiplying by the parameter $a[m]$ yield

$$a[m] \cdot x[n-m] = a[m] \cdot \sum_{k=1}^{M} \mathbf{h}_k \mathbf{z}_k^{n-m-1}. \tag{9}$$

The (9) can be modified to

$$\sum_{m=0}^{M} a[m] \cdot x[n-m] = \sum_{k=1}^{M} \mathbf{h}_k \mathbf{z}_k^{n-M} \left\{ \sum_{m=0}^{M} a[m] \cdot \mathbf{z}_k^{M-m-1} \right\}. \tag{10}$$

The right-hand summation in (10) may be recognized as a polynomial defined by (8), evaluated at each of its roots $\mathbf{z}_k$ yielding the zero result

$$\sum_{m=0}^{M} a[m] \cdot x[n-m] = 0. \tag{11}$$

The equation can be solved for the polynomial coefficients. In the second step, the roots of the polynomial defined by (8) can be calculated. The damping factors and the sinusoidal frequencies may be determined from the roots $\mathbf{z}_k$.

For practical situations, the number of data points N usually exceeds the minimum number needed to fit a model of exponentials, i.e., $N > 2M$. In the overdetermined data case, the linear equation (11) must be modified to

$$\sum_{m=0}^{M} a[m] \cdot x[n-m] = e[n]. \tag{12}$$

The estimation problem is based on the minimization of the total squared error

$$E = \sum_{n=M+1}^{N} |e[n]|^2 . \tag{13}$$

III. Min-Norm Method

The min-norm method involves projection of the signal vector

$$s_i = \begin{bmatrix} 1 & e^{j\omega_i} & \dots & e^{j(N-1)\omega_i} \end{bmatrix}^{\mathrm{T}}. \tag{14}$$

onto the noise subspace.

We consider a random sequence x made up of M independent signals in noise.

$$x = \sum_{i=1}^{M} A_i s_i + \eta, \quad A_i = |A_i| e^{j\phi_i}. \tag{15}$$

If the noise is white, the correlation matrix is

$$\mathbf{R_x} = \sum_{i=1}^{M} E\left\{A_i A_i^*\right\} s_i s_i^{\mathrm{T}} + \sigma_0^2 \mathbf{I} \tag{16}$$

where $\mathbf{I}$ denotes the identity matrix (matrix with 1s on the diagonal and 0s elsewhere), * denotes the complex conjugate, and $\{.\}^{\mathrm{T}}$ denotes the matrix transpose operation. $N-M$ smallest eigenvalues of the correlation matrix of dimension $N > M+1$ correspond to the noise subspace, and M largest value (all greater than σ_0^2) corresponds to the signal subspace.

We define the matrix of eigenvectors

$$\mathbf{E}_{\text{noise}} = [\mathbf{e}_{M+1} \quad \mathbf{e}_{M+2} \quad \dots \quad \mathbf{e}_N]. \tag{17}$$

Min-norm method uses one vector $\mathbf{d}$ for frequency estimation. This vector, belonging to the noise subspace, has minimum Euclidean norm and its first element is equal to one. These conditions are expressed by the following equations:

$$\begin{aligned} \mathbf{d} &= \mathbf{E}_{\text{noise}} \mathbf{E}_{\text{noise}}^{*\mathrm{T}} \mathbf{d} \\ \mathbf{d}^{*\mathrm{T}} \ell &= 1. \end{aligned} \tag{18}$$

We can express (18) in one equation

$$\mathbf{d}^{*\mathrm{T}} \ell = \left(\mathbf{E}_{\text{noise}} \mathbf{E}_{\text{noise}}^{*\mathrm{T}} \mathbf{d}\right)^{*\mathrm{T}} \ell = \mathbf{d}^{*\mathrm{T}} \mathbf{E}_{\text{noise}} \mathbf{E}_{\text{noise}}^{*\mathrm{T}} \ell = 1 \tag{19}$$

and form the Lagrangian

$$\begin{aligned} L = \mathbf{d}^{*\mathrm{T}} \mathbf{d} &+ \mu \left(1 - \mathbf{d}^{*\mathrm{T}} \mathbf{E}_{\text{noise}} \mathbf{E}_{\text{noise}}^{*\mathrm{T}} \ell\right) \\ &+ \mu^* \left(1 - \ell^{\mathrm{T}} \mathbf{E}_{\text{noise}} \mathbf{E}_{\text{noise}}^{*\mathrm{T}} \mathbf{d}\right). \end{aligned} \tag{20}$$

The gradient of (20) has the form

$$\nabla_{\mathbf{d}^*} L = \mathbf{d} - \mu \mathbf{E}_{\text{noise}} \mathbf{E}_{\text{noise}}^{*\mathrm{T}} \ell = 0 \tag{21}$$

where μ is chosen in such way that the first element of the vector is equal to 1. For this purpose, we present $\mathbf{E}_{\text{noise}}$ in the form

$$\mathbf{E}_{\text{noise}} = \begin{bmatrix} \mathbf{c}^{*\mathrm{T}} \\ \mathbf{E}'_{\text{noise}} \end{bmatrix} \tag{22}$$

where $\mathbf{c}^{*\mathrm{T}}$ is the upper row of the matrix. Hence, $\mathbf{c} = \mathbf{E}_{\text{noise}}^{*\mathrm{T}} \ell$.

From (21) and (22), it results that the first element of the vector $\mathbf{d}$ is equal to $\mu \mathbf{c}^{*\mathrm{T}} \mathbf{c}$. Finally, vector $\mathbf{d}$ is equal to

$$\mathbf{d} = \frac{1}{\mathbf{c}^{*\mathrm{T}} \mathbf{c}} \mathbf{E}_{\text{noise}} \mathbf{c} = \begin{bmatrix} 1 \\ \frac{(\mathbf{E}'_{\text{noise}} \mathbf{c})}{(\mathbf{c}^{*\mathrm{T}} \mathbf{c})} \end{bmatrix}. \tag{23}$$

Pseudospectrum, defined with the help of $\mathbf{d}$, is given as

$$\hat{P}(e^{j\omega}) = \frac{1}{|\mathbf{w}^{*\mathrm{T}} \mathbf{d}|^2} = \frac{1}{\mathbf{w}^{*\mathrm{T}} \mathbf{d} \mathbf{d}^{*\mathrm{T}} \mathbf{w}} \tag{24}$$

where $\mathbf{w}$ is defined as

$$\mathbf{w} = \begin{bmatrix} 1 & e^{j\omega_i} & \dots & e^{j(N-1)\omega_i} \end{bmatrix}^{\mathrm{T}}. \tag{25}$$

IV. Experiments With Simulated Waveforms

Several experiments were performed with the signal waveform obtained from a typical dc-arc-furnace plant of 80-MW nominal power [2]. The supply installation consists of a medium voltage ac busbar with two parallel thyristor rectifiers that are fed by a transformer secondary winding with Δ and Y connection, respectively. The investigated signal is characteristic for dc-arc-furnace installations without compensation. It consists of a basic harmonic (50 Hz), one higher harmonic (350 Hz), and one subharmonic (25 Hz) and is additionally distorted by a 5% random noise. The sampling interval was 1 ms. The signal was obtained by simulation based on real recordings.

The signal was investigated using the Prony and min-norm methods. Both the methods enable us to detect all the signal components using 50 samples (Fig. 1). For detecting the 25-Hz component using the Fourier algorithm, approximately ten times more samples were needed.

V. Industrial Frequency Converter

The investigated drive represents a typical configuration of industrial drives consisting of a three-phase asynchronous motor and a power converter composed of a single-phase half-controlled bridge rectifier and a voltage source converter. The waveforms of the converter output current under normal conditions (Fig. 2) were investigated using the Prony, the min-norm, and the FFT methods [11]. The main frequency of the waveform was 40 Hz.

Using the Prony and the min-norm methods, the following harmonics have been detected: fifth, seventh, 17th, 19th, 25th, 35th, and 41st. It is also possible to estimate the frequency of the fundamental component. Estimation of the main component frequency enables choosing an appropriate sampling window for the FFT.

VI. Out-of-Step Operation of a Synchronous Generator

If the machine running in parallel with others is disturbed from its synchronous-state conditions, the rotor-winding and the stator-winding fluxes rotate with different velocities. The stator-winding flux generates an electromotive force (EMF) in the rotor winding whose angular velocity depends on the rotor slip. The current in the rotor winding caused by the EMF produces a pulsating magnetomotive force (MMF), which can be resolved into two "rotating" MMFs of constant and equal amplitude revolving in opposite directions. These MMFs are assumed to set up corresponding gap fluxes. The angular velocities of the fluxes are equal to the angular frequencies of the alternating components of the rotor-winding current.

$$\omega_f = s \cdot \omega_s \qquad \omega_b = -s \cdot \omega_s \tag{26}$$

where ω_f is the angular velocity of the forward field component, ω_b is the angular velocity of the backward field component, ω_s is the angular velocity of the rotating stator field,

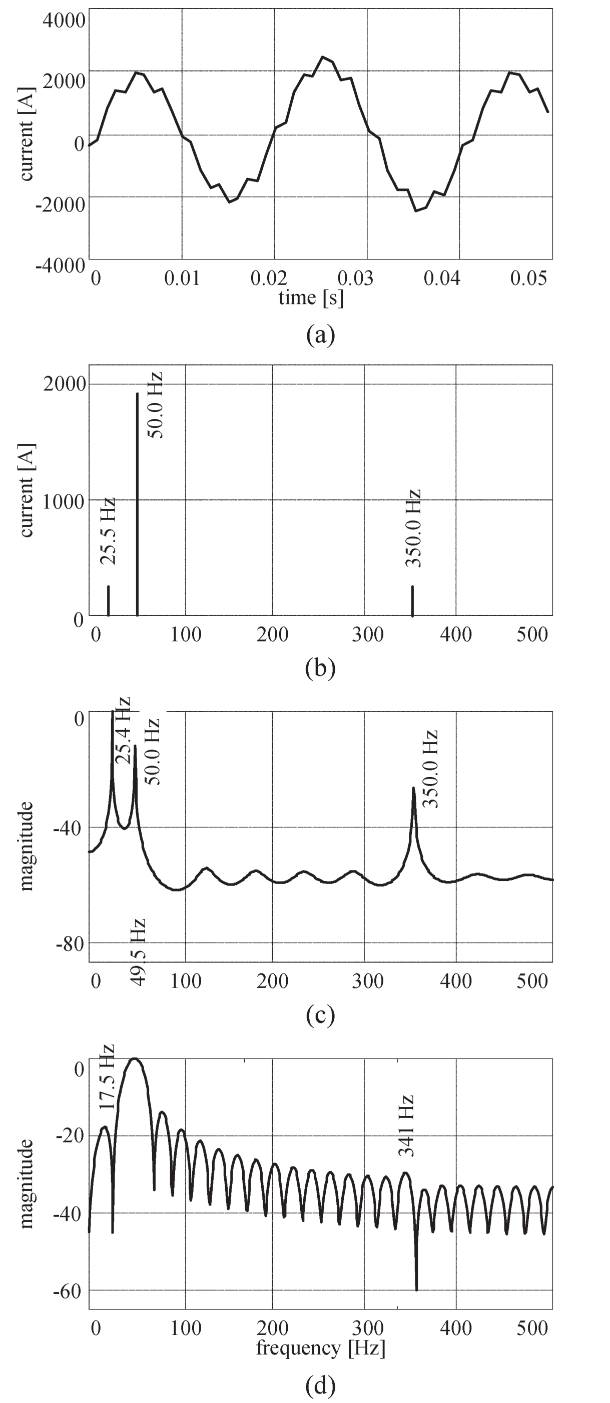


Fig. 1. Current waveform at the dc-arc-furnace plant investigation results. (a) Prony, $M = 10$. (b) Min-norm. (c) FFT. (d) $f_s = 1000$ Hz, $N = 50$, $f_s = 5000$ Hz.

and s is the rotor slip. The angular velocity of the rotor ω_r is described as

$$\omega_r = (1 - s)\omega_s. \tag{27}$$

The field components cut the stator conductors at velocities depending on the velocities of the components and the velocity of the rotor. Hence, corresponding EMFs are induced in the stator windings, causing current components to flow. The angular frequencies of the components are ω_s and $(1 - 2s)\omega_s$.

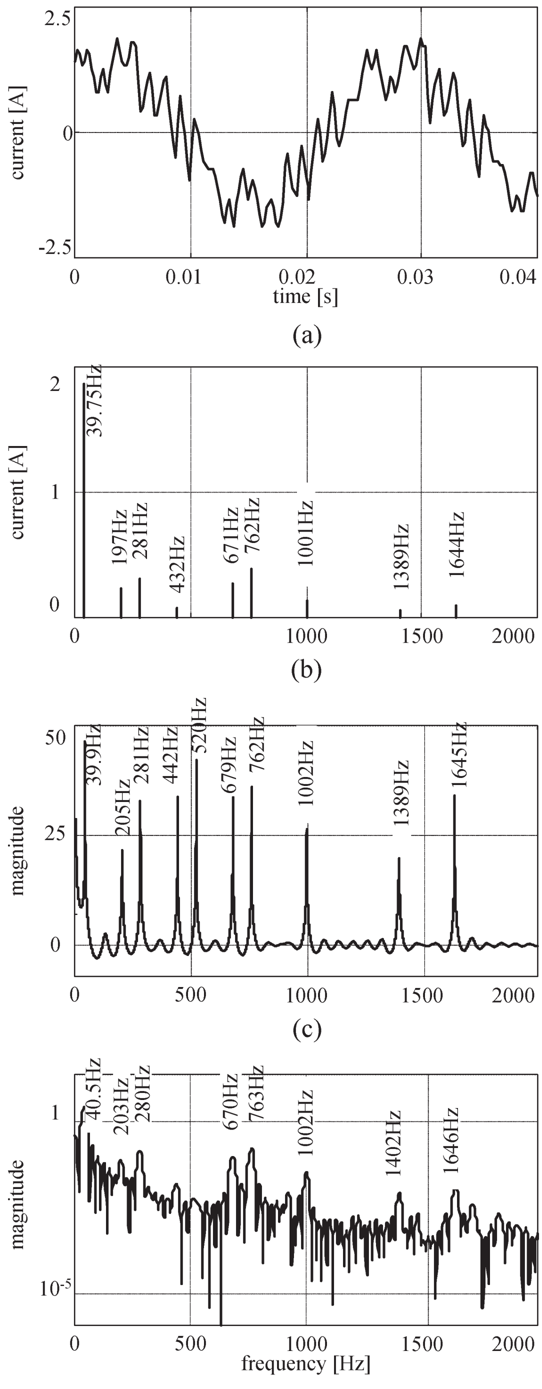


Fig. 2. Current waveform at the output of a real frequency converter investigation results. (a) Prony, $N = 200$, $M = 80$. (b) Min-norm, $N = 100$. (c) FFT, $N = 200$. (d) $f_s = 5000$ Hz.

Direct current in rotor windings produces MMFs, which set up corresponding gap fluxes. The fluxes rotate with the angular velocity ω_r, cut the stator conductors at sleep speed, induce corresponding UMFs, and cause another component of the stator currents.

A. Simulation of the Fault Operation

In the recent years, simulation programs for complex electrical circuits and control systems have been improved essentially. The Electromagnetic Transients Program—Alternative Transients Program (EMTP–ATP) as a FORTRAN-based and an MS-DOS/Windows adapted program serves for modeling complex one- or three-phase networks occurring in drive, control, and energy systems.

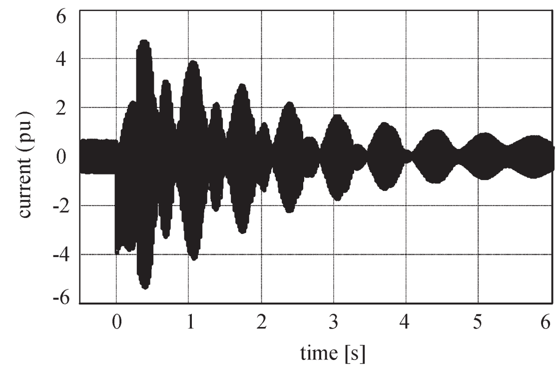


Fig. 3. Current waveform at the generator output. Duration of the fault is 300 ms (pu).

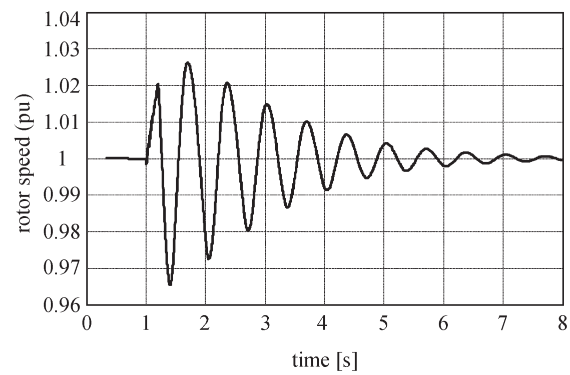


Fig. 4. Rotor speed of the generator during out-of-step operation (pu).

In this paper, we show investigation results of the fault operation of a synchronous generator powered by hydraulic turbine combined to a proportional-integral-differential (PID) governor system and an excitation system. The excitation system implements IEEE type-1 synchronous machine voltage regulator combined to an exciter.

Generator Data: Salient-pole synchronous generator: 200-MVA nominal power, 13.8-kV nominal voltage, and 50-Hz nominal frequency.

1) reactances: $X_d = 1.305$, $X'_d = 0.296$, $X''_d = 0.252$, $X_q = 0.474$, $X''_q = 0.243$ [per unit (pu)];
2) block transformer: 210 MVA, 13.8 kV/230 kV, dY, $R_1 = 0.0027$, $L_1 = 0.08$ (pu);
3) system: 10 GVA, 230 kV;
4) sampling frequency: 200 Hz.

Under normal steady-state conditions, a three-phase to ground fault at the transformer output was simulated. The fault was switched on at $t = 0$. After the fault was cleared, out-of-step operation conditions occurred. In Fig. 3, the current waveform at the generator output for the short-circuit duration of 300 ms is shown; and in Fig. 4, the rotor speed during the fault is shown. The time–frequency distribution of the waveform has been calculated by applying the min-norm method and the window of 40 samples (0.2 s).

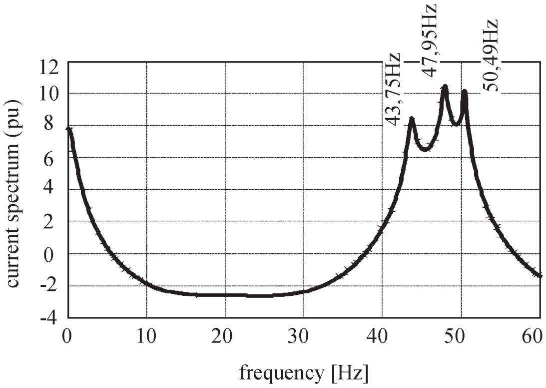


Fig. 5. Stator current spectrum of the signal in Fig. 3 for $t = 2$ s after fault incipience. Detected signal components with frequencies of 43.75, 47.95, and 50.49 Hz.

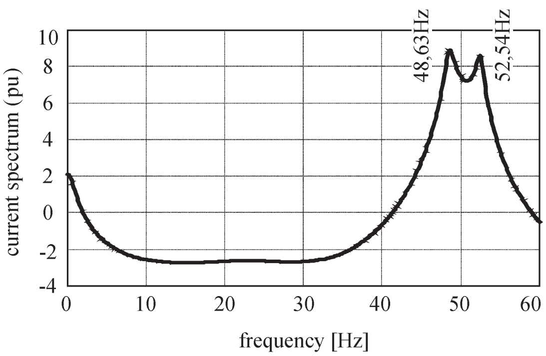


Fig. 6. Stator current spectrum of the signal in Fig. 3 for $t = 4$ s after fault incipience. Detected signal components with frequencies of 48.63 and 52.54 Hz.

In this way, a three-dimensional spectrum has been obtained. In this paper, only some cross sections of the spectrum are shown to demonstrate the high resolution of the method.

At the beginning of the asynchronous running, three current frequency components have been detected (Fig. 5). Afterward, the component with the smallest frequency disappeared (Fig. 6). The difference between the frequencies of the two other current components for $t = 4$ sec. is smaller than the value estimated for $t = 2$ sec. The decrease of the frequency differences of the signal components over time confirms the trend toward the retrieval of the generator from the out-of-step state.

VII. Conclusion

It has been shown that a high-resolution spectrum-estimation method such as min-norm could be effectively used for parameter estimation of distorted signals. The Prony method could also be applied for estimation of the frequencies of signal components.

The proposed methods were investigated under different conditions and found to be variable and efficient tools for detection of all higher harmonics existing in a signal. They also make possible the estimation of interharmonics. For identification of the asynchronous operation, the frequencies of the current components are estimated. The appearance of additional current frequency components can be used as an indicator of out-of-step operation of a synchronous machine. The decrease of the frequency differences of the detected current components over time indicates that the generator is leaving the out-of-step state.

References

[1] R. Carbone, D. Menniti, N. Sorrentino, and A. Testa, "Iterative harmonics and interhamonic analysis in multiconverter industrial systems," in *Proc. 8th Int. Conf. Harmonics and Quality Power*, Athens, Greece, Oct. 1998, pp. 432–438.

[2] A. Bracale, G. Carpinelli, D. Lauria, Z. Leonowicz, T. Lobos, and J. Rezmer, "On some spectrum estimation methods for analysis of non-stationary signals in power systems—Part II: Numerical applications," in *Proc. 11th Int. Conf. Harmonics and Quality Power*, Lake Placid, NY, Sep. 2004, pp. 6–16.

[3] K.-F. Eichhorn and T. Lobos, "Recursive real-time calculation of basic waveforms of signals," *Proc. Inst. Elect. Eng.*, vol. 138, Pt. C, no. 6, pp. 469–470, Nov. 1991.

[4] A. Cichocki and T. Lobos, "Artificial neural networks for real-time estimation of basic waveforms of voltages and currents," *IEEE Trans. Power Syst.*, vol. 9, no. 2, pp. 612–618, May 1994.

[5] Z. Leonowicz, T. Lobos, P. Ruczewski, and J. Szymanda, "Application of higher-order spectra for signal processing in electrical power engineering," *COMPEL—Int. J. Comput. Math. Electr. Electron. Eng.*, vol. 17, no. 5, pp. 602–611, Oct. 1998.

[6] T. Lobos, T. Kozina, and H. J. Koglin, "Power system harmonics estimation using linear least squares method and SVD," *Proc. Inst. Elect. Eng., Gen. Transm. Distrib.*, vol. 148, no. 6, pp. 567–572, Nov. 2001.

[7] M. Meunier and F. Brouage, "Fourier transform, wavelets, prony analysis: Tool for harmonics and quality of power," in *Proc. 8th Int. Conf. Harmonics and Quality Power*, Athens, Greece, Oct. 1998, pp. 71–76.

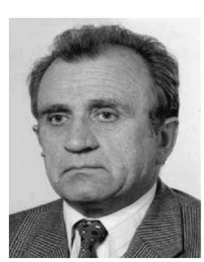
[8] S. M. Kay, *Modern Spectral Estimation: Theory and Application*. Englewood Cliffs, NJ: Prentice-Hall, 1988, pp. 224–225.

[9] T. Lobos and J. Rezmer, "Real-time determination of power system frequency," *IEEE Trans. Instrum. Meas.*, vol. 46, no. 4, pp. 877–881, Aug. 1997.

[10] C. W. Therrien, *Discrete Random Signals and Statistical Signal Processing*. Englewood Cliffs, NJ: Prentice-Hall, 1992, pp. 614–655.

[11] Z. Leonowicz, T. Lobos, and J. Rezmer, "Advanced spectrum estimation methods for signal analysis in power electronics," *IEEE Trans. Ind. Electron.*, vol. 50, no. 3, pp. 514–519, Jun. 2003.

[12] T. Lobos, Z. Leonowicz, and J. Rezmer, "Harmonics and interharmonics estimation using advanced signal processing methods," in *Proc. 9th Int. Conf. Harmonics and Quality Power*, Orlando, FL, Oct. 2000, vol. 1, pp. 335–340.



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